

Artificial Intelligence in Gambling Predictions: A 2026 Study for Moonbet Games

Abstract

Artificial intelligence (AI) is transforming gambling from a game of chance into a data-driven prediction problem. This research paper, prepared for **Moonbet Games** in 2026, examines how machine-learning models are used to forecast gambling outcomes, how market dynamics and human behaviour affect model performance, and how responsible-gambling tools can be integrated into AI systems. We review recent literature on prediction accuracy, calibration, profitability, match-fixing detection and responsible gambling. The study also synthesises market data showing that global gambling revenue exceeded **US\$643 billion in 2025** and is projected to rise above **US\$655 billion in 2026** [276500950160260†L72-L93] . Sports betting generated around **US\$82 billion in 2025**

[276500950160260†L95-L102] and advanced AI prediction systems are projected to drive an AI sports-betting market from **US\$10.8 billion (2025)** to more than **US\$60 billion by 2034** [576659712874176†L62-L70] . Our findings show that AI models achieve **70–85 % prediction accuracy** while human analysts rarely exceed **60 %**

[576659712874176†L62-L86] , yet profitability depends on model calibration and market efficiency [302602839336864†L52-L69] . We propose a hybrid framework combining prediction, market intelligence, calibration and player-safety modules and discuss future trends and regulatory considerations.

1. Introduction

The gambling industry has undergone rapid digital transformation over the last decade. Global gambling revenue surpassed **US\$643 billion in 2025** and is projected to exceed **US\$655 billion by the end of 2026** [276500950160260†L72-L93] , driven by online

betting and mobile platforms. In 2025, lottery and bingo generated **US\$346 billion**, casinos more than **US\$210 billion**, and sports betting about **US\$82 billion** [276500950160260†L95-L107] . Online gambling revenue reached **US\$121 billion in 2025** (around 20 % of total gambling turnover) and is expected to grow beyond **US\$123 billion in 2026** [276500950160260†L149-L156] . These trends highlight the scale of the market that AI now seeks to disrupt.

In the sports-analytics segment, the market is projected to exceed **US\$22 billion by 2030**, fuelled by AI adoption in leagues such as the NBA and Premier League [576659712874176†L62-L70] . The AI sports-betting market itself is growing from **US\$10.8 billion (2025)** to more than **US\$60 billion by 2034** (≈ 21 % CAGR)

[576659712874176†L62-L70] , reflecting the increasing reliance on machine-learning models by gamblers and bookmakers.

2. Literature Review

2.1 Machine-learning applications in gambling

A recent systematic review notes that machine-learning models—such as **support vector machines**, **random forests** and **neural networks**—are used to process historical data, in-game statistics and real-time information to optimise betting strategies [284616058074329†L53-L72] . These models enable **dynamic odds-setting**, exploit market inefficiencies and support fraud detection [284616058074329†L53-L72] . They also underpin the proliferation of micro-bets where gamblers wager on discrete in-game events

[362796629448114†screenshot] . Although bettors sometimes build simple algorithms to find value bets, gambling operators deploy much more sophisticated AI systems that analyse millions of data points and track user behaviour [362796629448114†screenshot] . This creates an **asymmetry of power**—AI has made gambling **smarter, faster and far more asymmetrical in who truly holds control**

[649648856943042†screenshot] .

2.2 Prediction accuracy and market efficiency

Machine-learning models have achieved impressive accuracy rates. Industry analysts report that modern AI models can predict game winners with **70–80 % accuracy** [576659712874176†L73-L86] and sometimes **75–85 %** [576659712874176†L82-L85] . A deep-learning

model described in a 2025 case study achieved **54.73 % accuracy** and an MCC (Matthews correlation coefficient) of **0.2666**, outperforming simpler baselines but not guaranteeing profitable bets

【88264621795660†L75-L88】. AI accuracy must be compared to human performance: seasoned analysts rarely exceed **60 % accuracy** because of cognitive biases and limited data processing
【576659712874176†L139-L145】.

However, high accuracy does not automatically translate into profits. SportBot AI warns that even if a model correctly predicts **75–85 %** of matches, betting success depends on identifying **value bets** where model-derived probabilities diverge from bookmaker odds

【88264621795660†L48-L50】. Studies show that betting markets are highly efficient; profits arise only when rare anomalies occur, and many machine-learning models hit a statistical ceiling

【88264621795660†L168-L171】. The **sports-betting revenue** of about **US\$88 billion in 2026** 【276500950160260†L176-L177】 reflects this efficiency, with operators earning through margins rather than prediction errors.

2.3 Calibration versus accuracy

Walsh & Joshi (2024) argue that calibration—the alignment between predicted probabilities and actual outcomes—is more important than raw accuracy for profitability. Using NBA data, they showed that selecting models based on calibration led to a **return on investment (ROI) of +34.69 %**, whereas models selected for accuracy produced – **35.17 % ROI** 【302602839336864†L60-L65】. The authors recommend that sports bettors optimise models for calibration rather than accuracy 【302602839336864†L60-L69】.

Additional evidence comes from Shams (2025), who tested XGBoost, LightGBM and Random Forest models on English Premier League data. While the models were statistically distinct from bookmaker odds, they **failed to generate consistent risk-adjusted returns**

【593327584158450†L68-L81】. Two factors were identified: **alpha decay**, where the predictive edge dissipated after 2015, and **calibration error** ($ECE \approx 0.11$), which caused risk-management strategies like the Kelly criterion to increase bankruptcy risk

【593327584158450†L68-L81】. These findings underscore that profitability in mature betting markets hinges on well-calibrated models and that the market has become more efficient

【593327584158450†L87-L116】.

2.4 Match-fixing detection and integrity

AI is not only used for predicting outcomes but also for safeguarding sports integrity. Kim et al. (2024) developed an **AI-based betting anomaly detection system** that uses logistic regression, random forests, SVM, k-nearest neighbours and an ensemble model to classify normal and abnormal matches based on betting odds. Their study constructed a real-time system using data from 12 betting companies and reported that **Random Forest, KNN and ensemble models achieved over 92 % accuracy**, while logistic regression and SVM achieved **approximately 80 %** [552455631410538†L108-L124] . The approach detects match-fixing anomalies by analysing betting patterns, demonstrating AI's role in maintaining fair play.

2.5 Responsible gambling and ethical concerns

The integration of AI into gambling raises ethical challenges. Mindway AI's neuroscience-informed system combines cognitive markers, machine-learning algorithms and expert assessments to monitor gamblers across **39 countries and 64 licensed jurisdictions** [161155991251326†L35-L41] . This hybrid approach tracks **over nine million players per month**, detecting early indicators of harm such as persistent high stakes, increased session duration, loss-chasing and deposit volatility [161155991251326†L35-L71] . By benchmarking players against population norms, the system reduces false positives and generates risk scores that trigger interventions [161155991251326†L79-L83] . However, the same behavioural data that enables early intervention can also be used for hyper-personalised marketing, raising privacy concerns. Responsible gambling frameworks therefore require explicit consent, data minimisation, human oversight, transparent profiling and clear separation between player-protection and commercial functions [161155991251326†L87-L100] .

The McMaster University article on AI and sports betting warns that **AI has not made gambling fairer but has made it smarter and faster** [649648856943042†screenshot] . The authors explain that gamblers may use simple algorithms to look for value bets, yet gambling companies deploy much more powerful AI systems that analyse **millions of data points** and monitor user behaviour, creating a feedback loop where the operator's AI optimises its counter-strategy [362796629448114†screenshot] . This asymmetry can exacerbate problem gambling and demands regulatory scrutiny.

3. Methodology

This Moonbet Games study synthesises published research, market reports and real-world case studies to analyse the state of AI in gambling prediction. Key steps include:

1. **Data collection:** We summarised market revenue statistics (global gambling, sports betting and online gambling) from industry data [276500950160260†L72-L107] [276500950160260†L149-L156] . We reviewed AI adoption figures and accuracy metrics from sports-analytics reports [576659712874176†L62-L86] and case studies [88264621795660†L75-L88] .
2. **Literature synthesis:** Academic studies were examined to understand model types, data inputs, calibration techniques and profitability results [284616058074329†L53-L72] [302602839336864†L52-L69] [593327584158450†L68-L81] .
3. **Responsible-gambling review:** We assessed responsible-gambling frameworks, player-monitoring tools and ethical considerations using industry analyses and news reports [161155991251326†L35-L83] [161155991251326†L87-L100] .
4. **Framework design:** Building on the literature, we propose a **Moonbet Hybrid Prediction Engine (MHPE)** that integrates prediction models, market intelligence, calibration and player-safety modules.

4. Results and Discussion

4.1 Market analysis and AI adoption

Table 1 summarises key market and performance metrics. The global gambling market is large and growing; sports betting contributes roughly **US\$82 billion** and online gambling around **US\$121 billion** [276500950160260†L95-L102] [276500950160260†L149-L156] . The AI sports-betting market is still nascent but expected to expand rapidly—from **US\$10.8 billion in 2025** to **> US\$60 billion by 2034** [576659712874176†L62-L70] . AI’s perceived value is reflected in adoption by bookmakers and third-party platforms that offer real-time probability updates, micro-bet suggestions and personalised betting tips. However, the **sports-betting revenue** of about **US\$88 billion in 2026** [276500950160260†L176-L177] suggests that the operator’s margin remains the main source of profits.

Table 1 – Key metrics for AI and gambling (black header/white rows)

Metric	Value
Global gambling revenue (2025)	US\$643 billion 【276500950160260†L72-L93】
Projected global gambling revenue (2026)	> US\$655 billion 【276500950160260†L72-L93】
Sports betting revenue (2025)	≈ US\$82 billion 【276500950160260†L95-L102】
Online gambling revenue (2025)	US\$121 billion 【276500950160260†L149-L156】
Projected online gambling revenue (2026)	> US\$123 billion 【276500950160260†L149-L156】
AI sports-betting market (2025)	US\$10.8 billion 【576659712874176†L62-L70】
Projected AI sports-betting market (2034)	> US\$60 billion 【576659712874176†L62-L70】
AI prediction accuracy (modern models)	70–85 % 【576659712874176†L73-L86】
Human analyst accuracy	≈ 50–60 % 【576659712874176†L139-L145】
Calibration-based ROI vs accuracy-based ROI	+34.69 % vs –35.17 % 【302602839336864†L60-L65】
Match-fixing detection accuracy (RF/KNN/ensemble)	> 92 % 【552455631410538†L108-L124】
Players monitored by Mindway AI per month	> 9 million 【161155991251326†L35-L41】

These metrics highlight the scale of gambling and the potential impact of AI-driven predictions. They also show that AI models are highly accurate but not necessarily profitable on their own, emphasising the importance of calibration and market intelligence.

4.2 Prediction accuracy of AI versus humans

AI models use high-dimensional data—player statistics, injuries, weather, referee tendencies and even social-media sentiment—to produce probability distributions for game outcomes

【88264621795660†L97-L115】. Modern platforms update these probabilities in real time, powering live odds and micro-bets

【576659712874176†L62-L86】. Such systems achieve **70–85 % accuracy** 【576659712874176†L73-L86】; some niche markets, like corner bets in Ligue 1, report **85 % accuracy** 【88264621795660†L137-L143】. However, accuracy varies across sports: MMA predictions may be only **52–60 % accurate** 【88264621795660†L137-L143】.

Human experts, in contrast, rely on limited variables and intuition. Traditional prediction methods—logistic regression, rule-based models and expert judgement—consider a handful of factors, often ignoring complex interactions and real-time updates. Cognitive biases (recency bias, favoritism, narrative fallacies) cap expert accuracy at about **50–60 %** 【576659712874176†L139-L145】. AI's ability to process thousands of variables and update predictions instantly therefore gives it a consistent edge 【576659712874176†L73-L86】.

4.3 Calibration and profitability

As emphasised in Section 2.3, calibration determines the profitability of AI predictions. Walsh & Joshi's study showed that NBA betting models selected for calibration yielded **+34.69 % ROI**, whereas accuracy-optimised models produced **–35.17 % ROI**

【302602839336864†L60-L65】. Shams (2025) found that even sophisticated models failed to generate profits because their **predictive edge decayed over time** and calibration errors caused overconfidence 【593327584158450†L68-L116】. These results highlight the adversarial nature of betting markets: bookmakers continually adjust odds to maintain margins, eroding any temporary advantage. Therefore, profitable AI betting requires **value detection**—comparing predicted probabilities with implied odds to find mispriced events 【88264621795660†L119-L127】.

4.4 Integrity and match-fixing detection

AI also enhances integrity monitoring. Kim et al. (2024) demonstrated that anomaly-detection models can identify match-fixing anomalies in real time with **over 92 % accuracy** using random forests, KNN and

ensemble methods [552455631410538†L108-L124] . Such systems learn betting patterns from historical odds and identify suspicious deviations. By implementing similar models, operators like Moonbet can detect fraud and maintain customer trust. AI-based integrity monitoring should operate alongside regulatory frameworks and independent oversight to avoid conflicts of interest.

4.5 Responsible gambling and player safety

Responsible gambling is a critical component of any AI-powered platform. Mindway AI's neuroscience-informed model combines cognitive metrics, machine learning and expert oversight to monitor over **nine million players per month** across **39 countries**

[161155991251326†L35-L41] . The system uses markers of harm—long sessions, high stakes, chasing losses and deposit spikes—to generate risk scores [161155991251326†L61-L71] . It also benchmarks players against population norms to reduce false positives

[161155991251326†L79-L83] . Such approaches show that AI can be used **proactively** to identify problem gambling before harm escalates.

Nevertheless, the same behavioural data can enable hyper-personalised marketing. Responsible frameworks must therefore enforce data minimisation, transparent profiling, human review of automated decisions and a strict separation between player-protection and commercial pipelines [161155991251326†L87-L100] . Regulators in the UK now require risk checks at thresholds of **£5 000 per month** or **£25 000 per year** [161155991251326†L113-L118] , and similar rules are being explored in other jurisdictions [161155991251326†L123-L134] . Moonbet should adopt privacy-by-design practices to build trust and comply with evolving regulations.

5. Proposed Moonbet Hybrid Prediction Engine (MHPE)

Drawing on the literature and market analysis, we propose the **Moonbet Hybrid Prediction Engine (MHPE)** (Fig. 1) with the following components:

1. **Data layer:** Aggregates historical match data, live statistics, injuries, weather, social-media sentiment and betting odds. The system should also integrate player-behaviour data (e.g., deposit frequency, session length) for responsible-gambling monitoring.

2. **Prediction layer:** Utilises ensemble machine-learning models (e.g., gradient boosted trees, neural networks) trained on the data layer to estimate outcome probabilities. Models should be calibrated using techniques such as Platt scaling or isotonic regression to align predicted probabilities with observed frequencies.
3. **Market-intelligence layer:** Continuously monitors bookmaker odds and market movements to identify value bets. This layer compares model probabilities with implied probabilities from odds and flags events where a significant discrepancy exists. It also tracks market liquidity and volatility to avoid thin markets susceptible to manipulation.
4. **Calibration engine:** Evaluates model outputs using proper scoring rules (e.g., Brier score) and recalibrates probabilities as needed. This engine also simulates betting strategies (flat stakes, Kelly criterion) to estimate ROI under different risk-management approaches.
5. **Responsible-gambling module:** Implements real-time risk-scoring algorithms inspired by Mindway AI. It analyses player behaviour to detect markers of harm and triggers interventions (e.g., time-out reminders, spending limits) before risk escalates. The module operates under strict privacy-by-design principles and is audited for fairness and transparency.
6. **Execution layer:** Interfaces with the betting platform to place bets, manage bankrolls and enforce responsible-gambling interventions. It logs all actions for auditability.

By integrating prediction, market intelligence, calibration and player-safety modules, MHPE aims to maximise predictive performance while maintaining integrity and protecting players.

6. Future Trends and Directions

Several emerging trends will shape AI-driven gambling over the remainder of the decade:

1. **Micro-betting and real-time analytics:** AI systems will enable betting on granular events (e.g., next point, next pitch) with continuous probability updates. These micro-bets increase engagement but also heighten the risk of problem gambling and require robust integrity monitoring.
2. **Generative AI and explainable predictions:** Large language models and generative networks can provide natural-language explanations of betting predictions, making AI more transparent and helping users understand the rationale behind model outputs.

Explainability could improve trust and support regulatory compliance.

3. **Blockchain-based fairness verification:** Immutable ledgers can record odds changes, bets and outcomes, enabling transparent audits and proving that betting models did not manipulate results. Coupled with zero-knowledge proofs, blockchain can enhance trust without exposing proprietary algorithms.
4. **Regulation and responsible innovation:** Jurisdictions are tightening rules on affordability checks, marketing and data use **【161155991251326†L113-L134】** . Future AI systems must embed compliance features—risk thresholds, human oversight and privacy safeguards—by design. Collaboration between regulators, academics and industry will be critical to balance innovation with consumer protection.
5. **Integration with prediction markets:** Decentralised prediction markets could serve as a complementary source of probabilistic information. AI models may combine market prices with proprietary predictions to improve calibration and identify arbitrage opportunities.

7. Conclusion

Artificial intelligence has introduced unprecedented analytical power to gambling, allowing platforms like Moonbet Games to process vast data sets and provide highly accurate predictions. Modern AI models reach **70–85 % accuracy** **【576659712874176†L73-L86】** —well above the **≈50–60 %** typical of human analysts **【576659712874176†L139-L145】** —and can dynamically adjust to new information. Yet, accuracy alone does not guarantee profits. Betting markets are increasingly efficient; predictive edges decay quickly, and mis-calibrated models can lead to losses **【593327584158450†L68-L116】** . Calibration, value detection and risk management are therefore essential.

AI also offers tools to safeguard sports integrity and player welfare. Anomaly-detection models achieve **> 92 % accuracy** in detecting match-fixing **【552455631410538†L108-L124】** , and responsible-gambling systems monitor millions of players to identify early signs of harm **【161155991251326†L35-L71】** . However, AI can exacerbate power asymmetries; operators wield highly sophisticated systems while gamblers often use simple algorithms

【362796629448114†screenshot】 . Responsible innovation, transparent regulation and privacy-by-design practices are required to ensure AI benefits the broader gambling ecosystem.

Overall, this research shows that AI can enhance predictive accuracy and efficiency in gambling but must be deployed thoughtfully. By adopting the MHPE framework, Moonbet Games can leverage AI's strengths—comprehensive data analysis, calibration and real-time market intelligence—while committing to fairness, integrity and player protection.

References

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